



A data-driven reassessment of the extreme coherent gust with direction change

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Abstract. The International Electrotechnical Commission (IEC) standard *Wind Turbines – Part 1: Design Requirements* defines an external condition known as the extreme coherent gust with direction change (ECD). This forms part of a design load case in which wind speed increases by 15 ms^{-1} and wind direction shifts by more than 60° over a 10-second period. Because of these abrupt changes, the ECD strongly influences the design of many wind turbine components, particularly the tower. As turbines have grown substantially in size over recent decades, the need to update these design standards has become increasingly pressing. In particular, questions have arisen over whether the ECD accurately captures the most extreme conditions experienced by modern turbines. This study therefore reassesses the ECD at a regional level, using data from 319 Vestas turbines operating across the globe. By treating each wind turbine as an anemometer, we find that wind speed and direction ramps are caused by thunderstorm outflows, also known as cold pools. While other mechanisms also cause ramps, cold pools most often show wind direction changes greater than 30° . Of the 75 events identified, none matched the ECD's defined characteristics. Furthermore, these events were concentrated in specific regions, notably the United States of America, Germany, Australia, and Argentina. Applying a probabilistic gust model to these four regions, we estimate the ECD's return period to be greater than 200 years – well above the 50-year return period intended by the standard. Comparing extreme loads from representative 50-year events in these regions to those produced by the ECD, we find a 28% reduction in the resultant bending moments at the bottom of the tower. These findings underscore an urgent need to redefine the ECD, and we believe this work provides a step in that direction.

1 Introduction

The extreme coherent gust with direction change (ECD) is an external condition defined in *Wind Turbines – Part 1: Design Requirements*, published by the International Electrotechnical Commission (IEC) (IEC, 2019). The gust is defined deterministically as a simultaneous change in wind speed and direction over a prescribed time interval. It serves as the external condition for design load case (DLC) 1.4 in the IEC standard, where the ECD is input to an aero-elastic solver to evaluate a turbine's dynamic response.

Although there is no general consensus on which meteorological phenomenon the ECD is intended to represent, it likely emulates the passage of a cold front or the downburst from a thunderstorm. Measurements from numerous onshore meteorolog-



ical masts shorter than 70 m were extrapolated to a 50-year return period to derive the ECD's defining properties: wind speed change, direction change, and rise time (Stork et al., 1998; Hansen et al., 2021). As a result of this definition, the ECD has been shown to have a substantial impact on the ultimate loads experienced by wind turbines. Indeed, DLC 1.4 is the design-driving load case for the towers of many turbine variants currently in operation.

Because the ECD directly affects production and maintenance costs, it has been the subject of extensive investigation. If events more severe than the ECD occur with meaningful likelihood, this increases the risk of premature component replacement. Conversely, an overly conservative load case can lead to inefficient designs and unnecessarily high material costs. Much of this uncertainty stems from the fact that the IEC standard was not originally developed with modern wind turbines in mind. In particular, the dataset used to derive the ECD came from onshore meteorological masts that were shorter than the hub heights of current turbines.

Since the derivation of this load case is not documented in the standard itself, Hansen and Larsen (2007) reanalysed the original dataset to validate the ECD's characteristics. They found that the wind speed change was well captured by the standard, but the direction changes were not as severe as predicted therein. Larsen and Hansen (2008) subsequently proposed a statistical method for deriving site-specific model parameters, though their approach assumes that such gusts are caused by boundary-layer turbulence. However, Hannesdóttir et al. (2019), analysing data from two meteorological masts separated by 400 m, showed that events resembling the ECD fall outside the envelope of the extreme turbulence model (IEC, 2019) and are instead driven by mesoscale phenomena. Hannesdóttir and Kelly (2019) later introduced a method for detecting and characterizing such events using the continuous wavelet transform, and applied it to measurements from three sites in Northern Europe. There, the events exhibited wind speed and direction changes comparable to those prescribed by the standard, but with rise times frequently exceeding 200 s. Building on this, Hannesdóttir et al. (2023) developed a probabilistic model to extrapolate measurements across the joint probability space of the three gust descriptors, obtaining a 50-year return surface. This joint probability distribution also allowed them to estimate the return period of the IEC ECD, which they found to be 460 years at a site on the west coast of Denmark.

While these studies establish a valuable framework for analysing ECD-like gust events, the severity of such events at sites with different climates remains an open question. Moreover, the underlying physical mechanisms driving these events have not been examined in depth. Notably, the gust extrapolation model may yield misleading results if events with distinct physical origins are combined into a single joint probability distribution. More recently, Abraham et al. (2026) addressed this limitation by analysing thunderstorm-driven outflow events in the Great Plains of the United States, where the observed gusts were likewise often slower than the ECD.

The link between thunderstorms and extreme changes in wind speed and direction is well established in boundary-layer meteorology (Stull, 2015; Simpson, 1999). Although different studies use varying terminology – gust fronts, downbursts or cold pools – these terms all describe the same underlying phenomenon: heavy precipitation from a thunderstorm rapidly cools a vertical column of air, creating a horizontal gradient in hydrostatic pressure that forces the air to flow radially outward from the storm as a gravity current (Benjamin, 1968; Charba, 1974; Garratt, 1984). When the direction of this outflow is misaligned with the ambient wind, the arrival of the gust front also produces a rapid shift in wind direction.



60 It should be noted that thunderstorms are not the only phenomenon capable of producing ECD-like wind conditions (Cook, 2023). Beyond mesoscale atmospheric processes, such events can also be driven orographically (Letson et al., 2019), an effect that has occasionally been observed in engineering practice as well.

The goal of this study is to use measurements from Vestas Wind Systems A/S's fleet of wind turbines to reassess the applicability of the extreme coherent gust with direction change across different sites worldwide. Note that our approach has a
65 key advantage: it defines the extreme conditions faced by the turbine using data from the turbines themselves. In doing so, our hypothesis is that the ECD is too conservative or in other words, it has a return period greater than 50 years at sites in simple or flat terrain. Hence, we build on the work presented in Patel et al. (2026), in which we used wind turbine operational data to reconstruct the rotor-averaged wind speed and introduced a workflow for detecting and characterizing such events across a fleet. Here, we extend this approach to a substantially larger set of turbines, aim to identify the physical mechanisms driving
70 the events, and extrapolate the measurements at a regional level. Finally, we present an analysis of gust-driven loads in both a measurement and simulation context.

The paper is organized as follows. Section 2 presents the methodology and data used in this study, including the reconstruction of the rotor-averaged wind speed, the geographical distribution of the turbines, the framework for extreme value extrapolation, and the generation of wind boxes for simulating gust-driven loads. Section 3 presents the results, beginning
75 with a classification of events according to their likely physical mechanism. We then focus on thunderstorm-driven events and examine their geographical distribution to highlight regions where they occur frequently, as well as regions where they are rare. This is followed by extreme value extrapolation of the gust variables in thunderstorm-prone regions. We also present measurements of gust-driven dynamic loads on turbine blades, along with aero-elastic simulations of the 50-year return surface. Finally, Sect. 4 presents the conclusions of the study and discusses its implications for future wind turbine design standards.

80 2 Methods

2.1 Definition of the extreme coherent gust with direction change

The ECD is defined in Sect. 6.3.3.6 of the IEC standards (IEC, 2019) as follows:

$$V(z, t) = \begin{cases} V(z), & \text{for } t \leq 0 \\ V(z) + 0.5 V_{cg} (1 - \cos(\pi t/T)), & \text{for } 0 \leq t \leq T \\ V(z) + V_{cg}, & \text{for } t \geq T, \end{cases} \quad (1)$$

where $V(z, t)$ is the time series of the gust at height z , $V_{cg} = 15 \text{ ms}^{-1}$ is the gust magnitude, $T = 10 \text{ s}$ is the rise time and $V(z)$
85 is the wind speed before the gust. It is recommended to simulate three wind speeds during load calculations: $V_r - 2$, V_r , $V_r + 2$

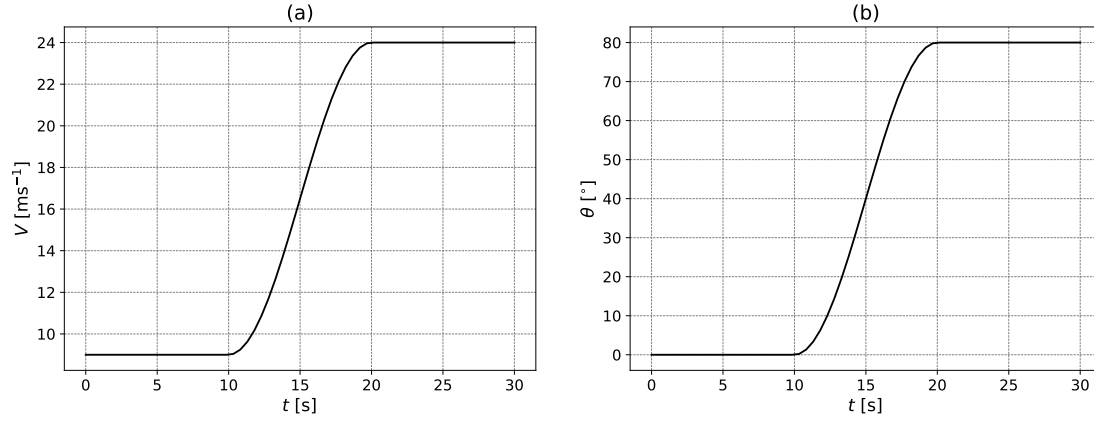


Figure 1. The time series of the wind speed (a) and wind direction (b) for the extreme coherent gust with direction change for a initial wind speed of 9 ms^{-1} , as specified in *Wind Turbines – Part 1: Design Requirements*, published by the International Electrotechnical Commission (IEC) (IEC, 2019).

ms^{-1} , where V_r is rated wind speed of the turbine. The time series of the wind direction change, $\theta(t)$, is given by:

$$\theta(t) = \begin{cases} 0^\circ, & \text{for } t < 0 \\ \pm 0.5 \theta_{cg} (1 - \cos(\pi t/T)), & \text{for } 0 \leq t \leq T \\ \pm \theta_{cg}, & \text{for } t > T, \end{cases} \quad (2)$$

where θ_{cg} is the magnitude of wind direction change:

$$\theta_{cg}(V_{\text{hub}}) = \begin{cases} 180^\circ, & \text{for } V_{\text{hub}} < 4 \text{ m/s} \\ \frac{720^\circ (\text{m/s})}{V_{\text{hub}}}, & \text{for } 4 \text{ m/s} < V_{\text{hub}} < V_{\text{ref}}. \end{cases} \quad (3)$$

- 90 Note that V_{ref} is the reference wind speed for the class to which the turbine belongs. The gust is also defined to be coherent over the entire rotor and the wind speed and direction changes happen simultaneously with zero lag. Lastly, this event is intended to have a return period of 50 years.

An example of the gust for $V_{\text{hub}} = 9 \text{ ms}^{-1}$ is shown in Fig. 1.

2.2 Summary of wind speed estimation

- 95 In this study, we use wind turbines as anemometers to measure the rotor-averaged wind speed, $\tilde{u}$. This is achieved by using 1 Hz measurements of the electrical power output, blade pitch, rotor speed and tower-top acceleration to solve the power balance relationship (Soltani et al., 2013). This method is henceforth referred to as the wind speed estimator (WSE) and our implementation has been described in detail in Patel et al. (2026).



Turbine specifications	Range
Rated power [MW]	3 - 9.5
Rotor diameter [m]	90 - 174
Hub height [m]	62 - 169

Table 1. The ranges of rated power, rotor diameter and hub height of the turbines whose data is analysed in this study.

Different variations of this method have been utilized for a long time in industrial wind turbines to estimate the wind speed for control purposes. To the best of our knowledge, our study is the first time the wind speed estimator has been used to detect and characterize gusts. Thus, in order to evaluate its biases for this use-case, we showed a comparison with a met-mast placed upstream of a prototype wind turbine in Patel et al. (2026). The wind speed change was underestimated by $1\text{--}2\text{ ms}^{-1}$ as compared to a cup anemometer placed at hub height. The cause of this discrepancy was found to be the torsional deflection of the blade at high wind speeds and a correction was included which reduced the difference in ΔU to less than 1 ms^{-1} . The rise time of the gust as seen from the WSE was also longer, when compared to that detected using the cup anemometer for events that had a "shear". During these "sheared" events, the wind speed change occurred 20 - 60 s earlier at the top of the rotor as compared to the bottom. Since no coherent events were observed in this dataset, we simulated them in an aeroelastic solver and found that there was no significant difference in the rise time detected from the WSE and from a point in the wind field five rotor diameters upstream of the turbine. These investigations led us to conclude that the WSE can accurately detect and characterize events like the ECD. Note that the wind direction changes are characterized using measurements from the sonic anemometers placed on the nacelle, which can show a directional bias up to 6° (Vanelli et al., 2026). In this paper, we aim to characterize wind direction changes that are an order of magnitude higher. Thus, biases of 6° or lower are not considered to be relevant here.

2.3 The dataset and data preparation

We use data from Vestas's onshore and offshore turbines. Their rated power output, rotor diameter and hub height are displayed in Table 1 where the ranges indicate the minimum and maximum values. In order to post process the data within a feasible amount of time, we only use turbines that are separated by at least 100 km. This results in a dataset of 319 turbines, which includes the 63 turbines analysed in Patel et al. (2026). The geographical distribution of these turbines is shown in Fig. 2. The figure shows that approximately 54% of turbines are in Europe with the rest present in North America (18%), Asia (11%), South America (9%) and Oceania (5%).

Although each turbine records a number of meteorological, operational, and control signals, only the signals used in this study are displayed in Table 2 with their sampling frequencies. The turbines retain data for a period of 1.5 years. However, the equivalent length of the entire dataset in time is greater than 1.5 years. This is achieved by combining the measurements from different turbines wherein the events are identically and independently distributed (i.i.d). The statistical model used to identify i.i.d data is described in Sect. 2.4. The data was collected over two different periods in time. Data from the 63 turbines

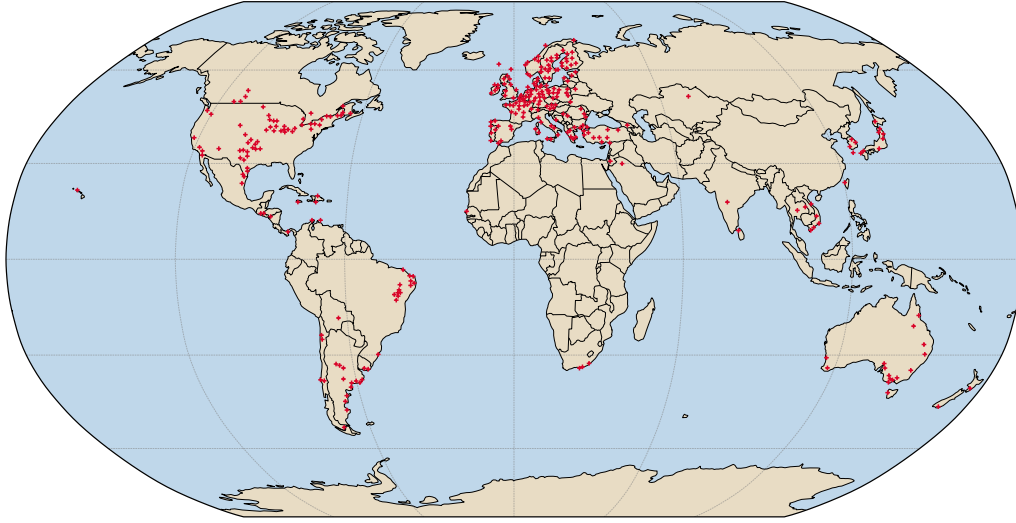


Figure 2. The location of turbines as indicated by the red dots. The data from these turbines was analysed in this study.

Signal	Symbol	Sampling frequency
Rotor-averaged wind speed [ms^{-1}]	$\tilde{u}$	1 Hz
Wind direction at hub height [$^{\circ}$]	θ	1 Hz
Mean ambient temperature at hub height [$^{\circ}\text{C}$]	T_a	10 min
Flapwise bending moment at root of the i -th blade [MNm]	M_f^i	10 min
Turbine operation state [-]	c	1 Hz

Table 2. The signals analysed in this study along with their sampling frequencies.

presented in Patel et al. (2026) was collected between April 2024 to October 2025. The additional 256 turbines analysed in this study recorded data between August 2024 to February 2026.

The workflow for processing data from each turbine was described in Patel et al. (2026) but is also repeated here. Note that the $\langle \cdot \rangle$ operator denotes a time average computed over a duration of 10 minutes.

1. The workflow starts with the analysis of 10 minute statistics of $\tilde{u}(t)$ and c , as defined in Table 2.
2. Those 10 minute periods are retained where $u_{in} < \langle \tilde{u} \rangle < u_{out}$ and the turbine is in operation for at least 1 minute. Note that u_{in} and u_{out} are the cut-in and cut-out wind speeds. The first criteria ensures the removal of data where the wind speeds are not within the operating regime of the turbine while the second condition filters out data where the turbine is not in production, even when the wind speed is between cut-in and cut-out (perhaps due to curtailment or maintenance).



- 135 3. Next, we select those 10 minute periods which correspond to the largest 1000 values of $\sigma_{\tilde{u}}$. As shown by Hannesdóttir et al. (2019), a large variance in the wind speed is often an indicator of a wind speed ramp.
4. Subsequently, to remove data corresponding to a ramp-down in wind speed, we retain only events for which the maximum of the wind speed occurs after the minimum, i.e., $\arg \max_i(\tilde{u}_i) - \arg \min_i(\tilde{u}_i) > 0$, where i is the time index. Events that do not satisfy this condition, wherein the wind speed instead decreases, are removed from the dataset. Note
140 that the $\arg \min$ and $\arg \max$ functions return the time index of the minimum and maximum respectively.
5. Hannesdóttir and Kelly (2019) suggest using $r \equiv \frac{\sigma_{\tilde{u}}}{\sigma_{\text{hpf}} + \beta}$, where σ_{hpf} is the standard deviation of the high-pass filtered velocity signal wherein the filter frequency, f_c , is $f_c = \frac{\langle \tilde{u} \rangle}{L}$ and $L = 2000$ m. Moreover, β is a constant equal to 1 ms^{-1} because it gives preference to extreme wind ramps that clearly stand out from background turbulence. The events are arranged in ascending order of r .
- 145 6. The method of Hannesdóttir and Kelly (2019) based on the continuous wavelet transform and curve fitting to the error function, is used to find the wind speed change (ΔU), the rise time τ_d and direction change ($\Delta \theta$). The time when the gust strikes the turbine, t_g , is also recorded.
7. Finally the top 10% of events are retained in the dataset where $\Delta U \geq 4 \text{ ms}^{-1}$, $\tau_d \leq 300 \text{ s}$ and the turbine is in operation when the event strikes the rotor.
- 150 After applying this procedure to all the turbines in the dataset and collecting the events, we excluded events wherein $\Delta U \geq 10 \text{ ms}^{-1}$ and $\tau_d \leq 100 \text{ s}$. This was done in order to focus the analysis on the most extreme events. Indeed, as shown in Sect. 3.5, it is the fast events with large changes in wind speed that are noteworthy from an aero-elastic perspective. In total, we found 356 events. These will be analysed further in the next section.

2.4 Framework for extreme value extrapolation

- 155 In order to assess whether the ECD represents the 50-year event, we use the probabilistic model presented by Hannesdóttir et al. (2023). This method estimates the joint probability distribution of the three gust variables: ΔU , τ_d and $\Delta \theta$ wherein the joint distribution is represented by the Nataf model (Liu and Der Kiureghian, 1986). The Nataf transform (Nataf, 1962) converts a set of random variables, wherein each variable is represented by an arbitrary marginal distribution, into correlated standard normal variables with a Gaussian copula. Thus, the inverse Nataf transform can be used to estimate the distribution of the
160 50-year return surface in the original space of the gust variables. This is achieved by calculating an exceedance probability and defining a joint distribution in uncorrelated standard normal space using the inverse second-order reliability method (ISORM) (Chai and Leira, 2018). Since the variables have no correlation, the joint distribution is sphere. Then, marginal distributions are fitted to the data and the correlation coefficients are determined. The correlation coefficients are corrected based on the suggestions of Liu and Der Kiureghian (1986). They are subsequently used to transform the sphere to correlated standard
165 normal space. The last step involves using the inverse Nataf transform to obtain the joint distribution or return surface in the probability space of the three gust variables. Each point on this surface has the same likelihood of occurring once in 50 years.



Note that the return period of the ECD for the given set of measurements, can also be determined by inverting the procedure described above. Since it is pertinent to the discussion that follows, we explain the calculation of the exceedance probability herein. For other details of the model, we refer the reader to Hannesdóttir et al. (2023).

170 We wish to calculate the probability of one event occurring in 50 years, P_e . In other words, P_e is the probability that one event exceeds the intensity of all events expected to occur over 50 years. When dealing with regularly distributed data, this exceedance probability can be defined as:

$$P_e = \frac{T_0}{T_{50}}, \quad (4)$$

wherein T_0 is the reference period and T_{50} is the 50-year return period with the same unit as T_0 . If the unit of T_0 is 10 min
 175 periods, then $P_{50} = \frac{1}{50 \times 365 \times 144} = \frac{1}{2.628 \times 10^6}$. However, when the data are irregularly distributed, P_e cannot be calculated by Eq. 4. This is because the number of events detected over 50 years no longer equals 2.628×10^6 . Indeed, the denominator of Eq. 4 must be adjusted based on the occurrence rate of events, f_a . If N_e events are detected from a campaign that spans T_m years in time, then:

$$f_a = N_e \frac{T_0}{T_m}. \quad (5)$$

180 Thus, the exceedance probability is now given by:

$$P_e = \frac{T_0}{T_{50} f_a} = \frac{T_m}{T_{50} N_e}, \quad (6)$$

where T_0 , T_{50} and T_m are in the same units.

Hannesdóttir et al. (2023) applied the gust model to $N_e = 92$ events detected over $T_m = 10.25$ years at one site. However, our dataset includes 1.5 years of measurements from many different sites. Thus, we are faced with a choice between two extremes.
 185 On one hand, if we apply the probabilistic model to all 319 sites/turbines, then we can assess the site-specific conservatism of the ECD at a very high resolution. But due to limited amount of data per site spanning only 1.5 years in time, the results would have significant uncertainty. On the other hand, we could consider the entire globe as one site, assume events separated by a certain distance to be independent of each other and increase T_m to a value larger than 1.5 years. However, this solution is also not optimal as it does not utilise the potential of our dataset to refine the ECD on a more region or site specific level. It also
 190 does not account for the fact that wind speed ramps are more frequent and severe in certain parts of the world, as shown in Patel et al. (2026). Given these issues, we believe the following is the optimal way of applying the probabilistic model to the data.

We first segregate events based on the meteorological cause. Not only does this give a more physical basis to the statistical model, it also helps exclude events that do not produce wind conditions like the ECD. As discussed in Sect. 3.1, the outflow
 195 from a thunderstorm creates large changes in wind speed and direction, similar to the ECD. Hence, we assess the likelihood of a thunderstorm-driven gust emulating the ECD. Next, the dataset is further segmented into different regions or countries where thunderstorm-driven events were found. This brings together events that occur under the same climate while commenting on the applicability of the ECD in various countries.



However, we still cannot apply the probabilistic model to the events detected in a particular country because we do not know if those events are identically and independently distributed and the T_m of the resultant dataset. It is well established in extreme value theory that rare exceedances from an i.i.d. sequence converge to a Poisson distribution (Leadbetter et al., 1983). This theorem has been previously used to define gusts by Kristensen et al. (1991). The converse theorem is also true and hence, in our case, if the events are i.i.d., we would expect the number of sites (S) with k events to follow a Poisson distribution, $P(k)$, such that:

$$P(k) = \frac{\lambda^k \exp(-\lambda)}{k!}, \quad (7)$$

and,

$$S(k) = P(k)S_T \quad (8)$$

where λ is the average rate of occurrence of events at a given site and S_T is the total number of sites. We attempted to fit Eq. 7 to all sites in a particular region which resulted in a poor fit with the data. However, if we fit the distribution to only those sites with one or more events, we obtain a fit wherein the mean-square-error, $RMSE$, is less than 0.4. Note that:

$$RMSE = \frac{1}{N_k} \sum_{k=1}^{N_k} \sqrt{S_{meas}^2 - S_{fit}^2}, \quad (9)$$

where $N_k = 6$. We estimate λ by solving the following relation:

$$E(k|k > 0) = \frac{\lambda}{1 - \exp(-\lambda)}, \quad (10)$$

where $E(k|k > 0)$ is the conditional expectation of events at sites where one or more events were detected. In other words, it is the ratio of the number of events detected in a region to the number of sites where an event was detected. After estimating λ and checking the quality of the fit, we can calculate S_T :

$$S_T = \frac{S(k > 0)}{1 - \exp(-\lambda)}. \quad (11)$$

Finally, we can approximate the length of the dataset in time for a given region:

$$T_m = 1.5S_T. \quad (12)$$

Thus, by sub-sampling our data using a Poisson distribution, we apply the probabilistic gust model on region-specific level. The entire process is summarized in Fig.3. We acknowledge that sub-sampling the data in a given region and excluding some sites with zero events from the statistical analysis might seem arbitrary. However, this procedure is arguably conservative. If we were to include, for instance, all 52 sites in the United States of America (10 sites with events and 42 without), then $T_m = 1.5 \times 52 = 78$ years. Therefore, the 50-year event would be less intense than the measurements.

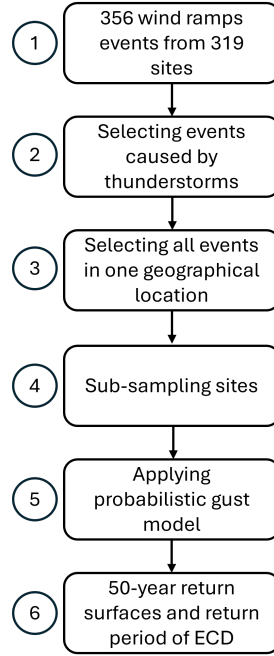


Figure 3. An overview of extreme value extrapolation for the three gust parameters: wind speed change (ΔU), rise time (τ_d) and direction change ($\Delta\theta$).

2.5 Generation of wind boxes for aeroelastic simulations

In the next section, we will present load simulations wherein the gust will be provided as input to the aeroelastic solver. This is achieved by generating a turbulence box using the algorithm described in Mann (1998) and implemented in Dimitrov et al. (2024). Then, the turbulence fluctuations are added to the time series of the gust which in this case describes the mean wind or the non-turbulent part:

$$\mathbf{u}_p(x, y, z) = \mathbf{u}_m(x, y, z; \alpha\epsilon^{2/3}, L, \Gamma) + \mathbf{e}_x U(x) \cos \theta(x) + \mathbf{e}_y U(x) \sin \theta(x), \quad (13)$$

where $\mathbf{u}_m$ is the turbulence box with parameters L , Γ and $\alpha\epsilon^{2/3}$. We use $L = 80$ m and $\Gamma = 3$. The scaling parameter, $\alpha\epsilon^{2/3}$, is determined via (Kelly, 2018):

$$\alpha\epsilon^{2/3} = 0.44\sigma_1^2 L^{-2/3}, \quad (14)$$

with $\sigma_1 = 1 \text{ ms}^{-1}$.

The unit vectors, $\mathbf{e}_x$ and $\mathbf{e}_y$, are in the along-wind and cross-wind directions respectively. The non-turbulent wind speed $U(x)$ and direction $\theta(x)$, are modelled using:

$$U(t) = \frac{U_b + U_a}{2} + \frac{U_a - U_b}{2} \operatorname{erf}\left(\frac{t - t'}{\tau_d}\right), \quad (15)$$



$$\theta(t) = \frac{\theta_b + \theta_a}{2} + \frac{\theta_a - \theta_b}{2} \operatorname{erf}\left(\frac{t - t'}{\tau_d}\right), \quad (16)$$

such that subscripts "b" and "a" indicate wind speed or direction before and after the gust respectively. Thus, $\Delta U = U_a - U_b$ and $\Delta\theta = \theta_a - \theta_b$. Moreover, τ_d is the rise time. The error function, erf, is the same as the one used to find the rise times and amplitudes from the measurements. Note that Taylor's hypothesis is used to convert the time-series into a space-series (the negative sign has been dropped for convenience):

$$x = \bar{U}t, \quad (17)$$

wherein,

$$\bar{U} = \frac{1}{T} \int_0^T U(t) dt. \quad (18)$$

The wind boxes containing the gusts sampled from the 50-year return surface are provided as input to the aero-elastic solver VTS (Vestas turbine simulator). It is a state of the art blade element and momentum theory (BEM) solver derived from Flex5 (Øye, 1996) and based on the mode shape approach using generalised coordinates, masses, stiffnesses and forces. The solver is non-linear as mass, damping and stiffness matrices are recalculated at every time step. It includes tip loss correction, a dynamic stall model and is linked to the controller via a dynamic-link library (DLL). Note that the solver uses the same controller as the real turbine.

3 Results

3.1 Investigation of the driving mechanism

We first investigate the cause of all 356 events using data not only from the turbines but also from publicly available radar scans, national records of named storms passing through a particular region and terrain data. We are able to identify three mechanisms that cause the events. These include outflow from a thunderstorm or a cold pool, tropical or extratropical cyclones and flow in complex terrain. Thunderstorms are identified by a drop in temperature of at least 2 °C occurring in the same 10 min period as the wind speed and direction changes (Abraham et al., 2026). We refer the reader to Appendix A for the motivation for using this criteria. Where available, we also check historical radar scans from the same period in time (Müller and Floors, 2026; NOAA National Centers for Environmental Information, 2026). Herein, we observe rainfall within a few kilometres of the turbine location as well as a bow echo in some cases. Note that we did not exclude events where no precipitation was observed in the radar scans. Overall, 75 events are caused by thunderstorms.

We analyse the time-series of $\tilde{u}$ for the remaining 281 events in decreasing order of the corresponding values of r (computed in step 5 of the procedure shown in Sect. 2.3). We segregate those events wherein we observe a ramp in the wind speed. Beyond a certain value of r , the events do not show a wind ramp but rather very turbulent conditions with rapid changes in wind speed.



Cause	N_c
Outflow from a thunderstorm	75
Extratropical cyclone or tropical depression	239
Complex terrain	23
Unknown	21

Table 3. The physical mechanisms which drive the extreme wind speed and direction changes observed in the fleet data along with the number of such events, N_c , in each class.

As shown by Table 3 and Fig. 4, they are not comparable to the ECD. We also find that these events occur around the same time as named storms pass through the respective regions. Thus, 237 events are caused by extratropical cyclones or tropical depressions.

From the 44 events with a wind ramp that were not caused by thunderstorms, 27 occur in complex terrain. Hence, we believe that there are probably driven by terrain effects. The cause of 17 events could not be identified. They might be caused by an interfacial gravity wave occurring when the boundary layer height close to the hub-height of the turbine or another unidentified mechanism.

A summary of the different classes of events is provided in Table 3 while Fig. 4 shows some examples.

The rest of this paper will focus on the analysis of the 75 events which were caused by the outflow from a thunderstorm. This is because they create wind conditions that are similar to the ECD with wind direction changes often exceeding 30° . Indeed, as shown in Fig. 4, the wind speed and direction during an extratropical cyclone do not resemble a ramp. They could be compared to the extreme turbulence model (ETM) (IEC, 2019) which is outside the scope of this study. Terrain driven events are also comparable to the ECD. However, we do not record enough events in order to apply the probabilistic gust model. Finally, the 17 events with an unidentified cause did not showed direction changes less than 30° .

3.2 Geographical distribution

The geographical distribution of the cold pool events is shown in Fig. 5. We observe that the events are concentrated in four regions: United States of America, Argentina, Australia and Germany. The number of events in these four regions are presented in Table 4.

The prevalence of cold pool events in these regions does not come as a surprise as the most intense convective storms tend to occur there (Zipser et al., 2006; Rasmussen et al., 2014; Smith et al., 2013). Indeed, in Argentina and United States of America, cold air from the poles can freely mix with warm air from the tropics because the prominent mountain ranges in these regions are not aligned east to west. Moreover, a strong vertical wind shear in these regions can decouple the updraft from the downdraft. Together, these conditions are favourable for the formation of long-lived mesoscale convective systems (Stull, 2015) which can spawn tornadoes, cause heavy precipitation and lead to high speed straight-line winds at the gust front. On the other hand, events observed in Australia are likely not caused by convective storms. During spring and summer, the orographically-forced Southerly Burster (Colquhoun et al., 1985) leads to rainfall and dust storms along the western coast of

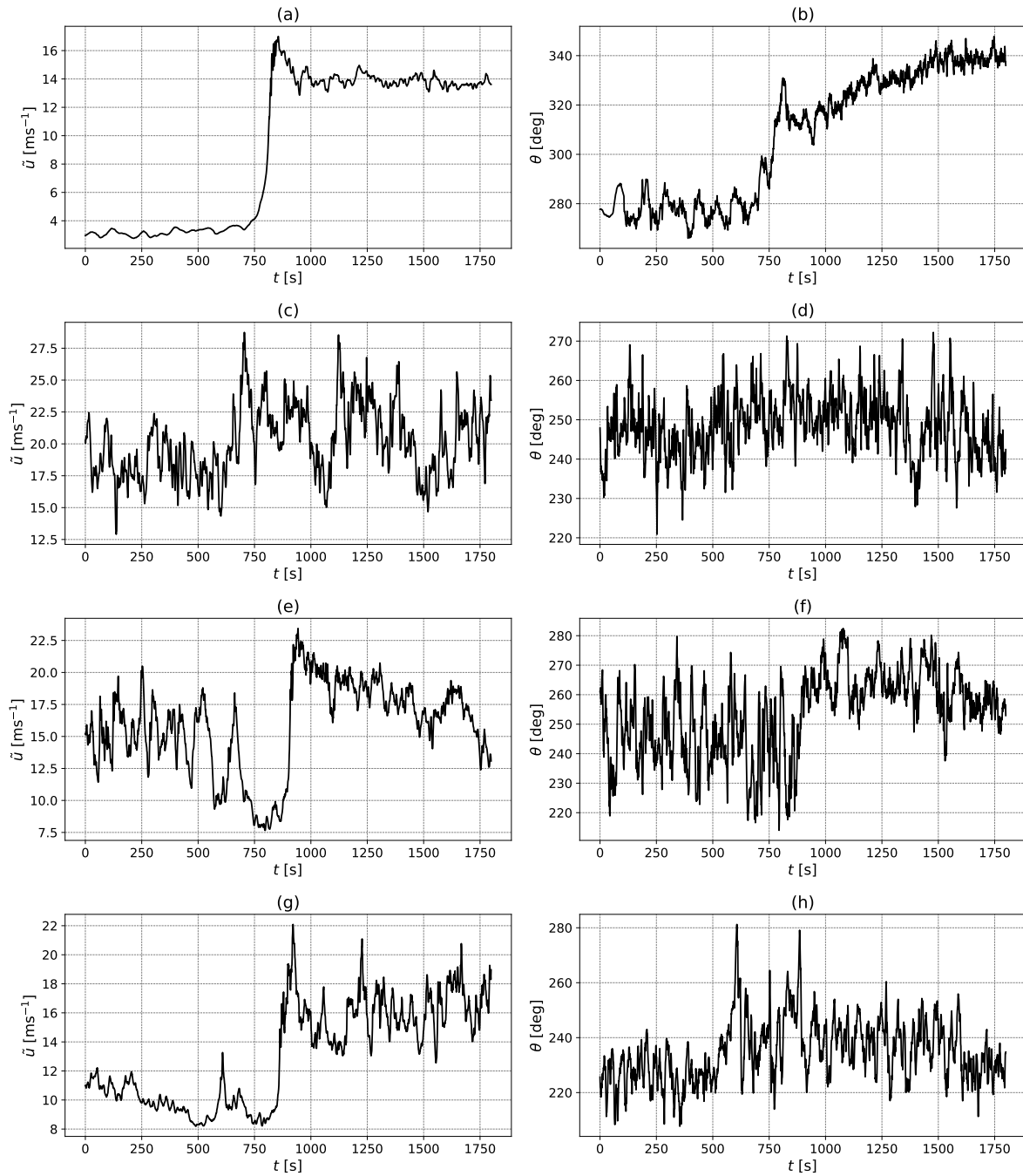


Figure 4. Typical time series of the rotor-averaged wind speed ($\tilde{u}$) measured by the wind speed estimator and wind direction from the nacelle anemometer (θ) during cold pools or outflow from a thunderstorm (a, b), an extratropical cyclone (c, d), a gust in complex terrain (e, f) and an event whose cause could not be identified (g, h).

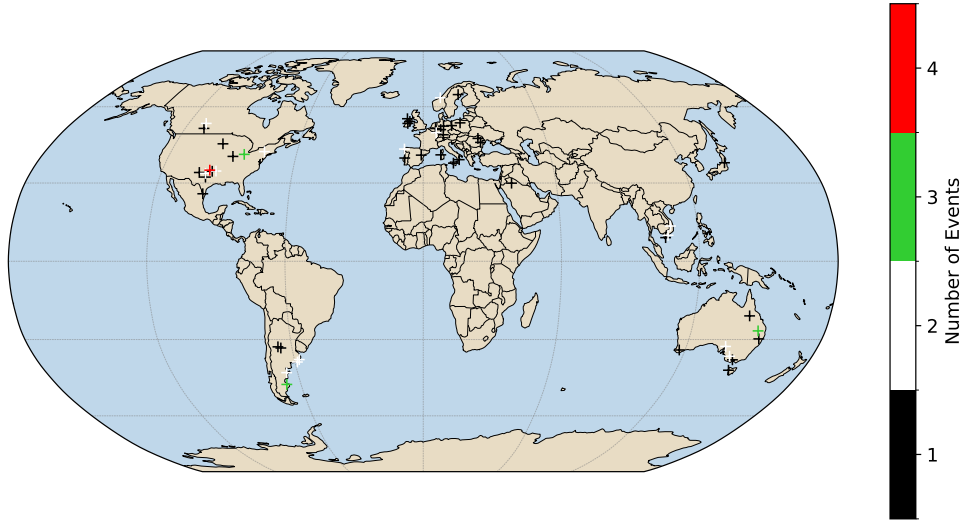


Figure 5. The geographical distribution of the events which were caused by cold pools or gravity currents originating from a thunderstorm.

Australia. Indeed, 66% of the events in Australia occur during spring and autumn. Events in United States, Argentina and Germany mostly occur during summer and spring, when thunderstorm activity peaks in these regions (Smith et al., 2013).

We can also comment on the scarcity of events in some parts of the world. Based on the four regions identified earlier, we
 295 can calculate the mean rate of occurrence of events per site, μ ,:

$$\mu = \frac{1}{4} \sum_{r=1}^4 \frac{N_{e,r}}{S_r}, \quad (19)$$

where $N_{e,r}$ is the number of events detected in the region with S_r sites. Then, the expected number of events in a given site, $\hat{N}$, can be approximated as:

$$\hat{N} = \text{round}(\mu S_r). \quad (20)$$

300 In Table 5, we show that there are many regions where the occurrence of events is far below the rate expected based on the measurements from the other four regions.

3.3 Characteristics of the events

Figure 6 presents the wind speed change, rise time and direction change of all the cold-pool events. We observe events that have wind speed and direction changes that are comparable to the ECD but with slower rise times. On the other hand, the



Region	N_e
United States of America	18
Argentina	11
Australia	12
Germany	7

Table 4. The number of cold pool events, N_e , detected in United States of America, Argentina, Australia and Germany.

Region	$N_{e,r}$	$\hat{N}$
Brazil	0	8
France	0	10
Sweden	1	8
Turkey	0	7
Finland	0	7
United Kingdom	0	7
Norway	2	6
Japan and South Korea	1	7

Table 5. The number of events detected in the respective regions ($N_{e,r}$) compared to the number of expected events ($\hat{N}$) obtained by multiplying the mean rate of occurrence per site in Table 4 with the number of sites in the respective regions.

fastest event has $\tau_d = 14$ s but with $\Delta U = 10.5 \text{ ms}^{-1}$ and $\Delta\theta = 74^\circ$. Generally, 57 % of events have rise time slower than 60 s while the median wind speed change is 11.3 ms^{-1} .

We also detect a delay between the changes in wind speed and direction. Hence, we define t' as the difference in time between the position of fastest change in wind direction and wind speed such that t' is negative when the wind direction change occurs earlier. The distribution of t' over all 75 events is shown in Fig. 7. Herein, we observe that in 68% of events, the wind direction changes before the wind speed. Moreover, the delay can be up to ± 80 s. Similar observations have been made in previous studies of thunderstorm outflows (Abraham et al., 2026; Wakimoto, 1982), although the physics behind them remains unexplained.

We tried to identify a "shear" in the gusts. This refers to the observations made during the validation of the wind speed estimator in Patel et al. (2026) wherein some events arrived earlier at the top of the rotor compared to the bottom. In that study, detecting this shear was trivial as the turbine was a prototype with an up-stream met-mast. However, this is more challenging in the fleet data as we do not possess wind speed measurements at multiple heights. Instead, we attempt to detect the shear by comparing the measurements of the events from the nacelle anemometer to the wind speed estimator. As shown in Patel et al. (2026), for a non-zero shear, the rise time of the event will be slower in the wind speed estimator compared to the point-like measurement from an anemometer.

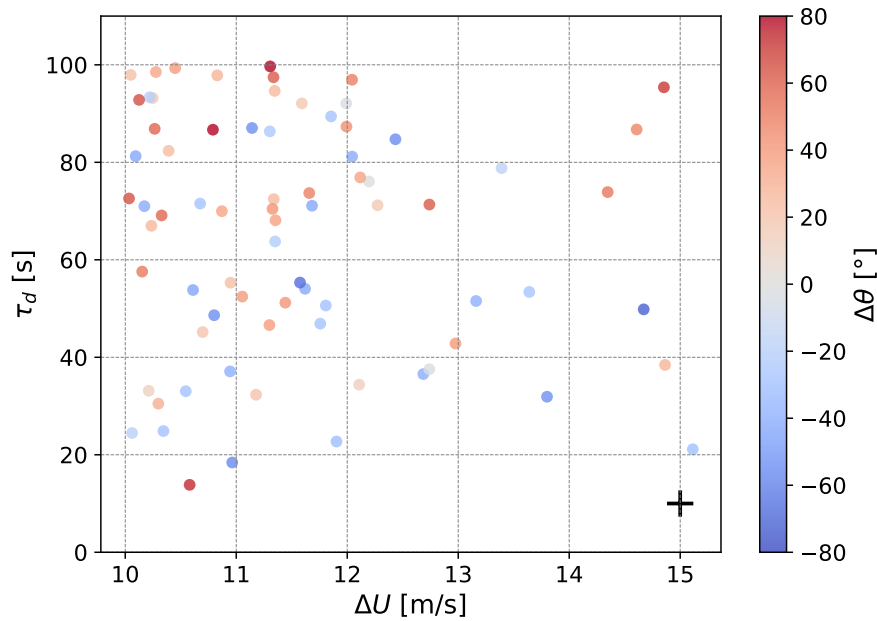


Figure 6. The wind speed change ΔU , rise time τ_d , and wind direction change $\Delta\theta$ for the 75 cold pool events. Note that the wind speed change and rise time of the ECD is indicated by the black cross ('+').

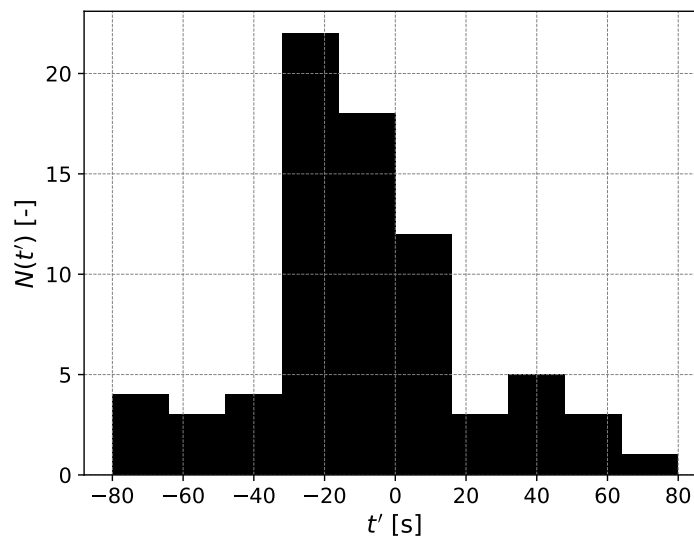


Figure 7. A histogram of the delay t' between wind speed and direction changes for the 75 cold pool events. A negative delay corresponds to the wind speed changing after the wind direction.



320 We first attempted to apply this analysis to 19 out of the 75 events which were detected from the 63 turbines presented in Patel et al. (2026). In 2 out of the 19 events, we detected a significant difference in τ_d between the wind speed estimator and nacelle anemometer. The rise times from the WSE were 99 s and 71 s whereas those from the nacelle anemometer were 59 s and 16 s respectively. However, in most cases we were unable to reach a definitive conclusion due to the level of noise in the anemometer measurements which lead to a poor fit with the error function profile, as part of the gust characterization procedure
325 outlined in Hannesdóttir and Kelly (2019).

In the following sections, we assume that all gusts are coherent. This assumption is conservative from the perspective of aero-elastic loads as shown in Appendix B. Herein, we observe that a coherent gust with a 20 s rise time causes a sharp increase in the tower-bottom resultant moment while a sheared gust with $\tau_d = 10$ s and 20 seconds of shear does not have a similar impact. The results are likely explained by fact that the controller can anticipate the sheared gust using data from the upper part of the
330 rotor and then take appropriate load-mitigation actions. In case of the coherent gust, there is no "early-warning".

3.4 Extreme value extrapolation

We now apply the extreme value extrapolation framework outlined in Sect. 2.4 to the data from the four regions. First, a Poisson distribution was fitted to the number of sites, $S(k)$, where $k > 0$ events were detected. The results are presented in Fig. 8 and Table 6 wherein the root mean square error between the data and the fit, $RMSE$, is below 0.4 in all four cases. This shows
335 that the events in a given region are independently and identically distributed. Moreover, the equivalent length of the dataset in time can be approximated using Eq. 11 and 12. The values of T_m , S_T and λ the four regions are also shown in Table 6.

Next, we applied the probabilistic gust model developed by Hannesdóttir et al. (2023). Marginal distributions were fit to the three gust descriptors. Figure 9 shows results of the fit along with the family of extreme value distributions that were selected for the three gust parameters measured in the United States of America. Then, knowing T_m , we calculated the exceedance
340 probability and with it the reliability index, β , using the inverse second order reliability method (ISORM) (Dimitrov et al., 2024). This allows us to find the gust return surface in uncorrelated standard normal space. Using the Nataf transform and knowing the marginal distributions, the return surface can be obtained in the joint space of the three gust variables. Note that we set the correlation matrix, R , as a 3 x 3 identity matrix. This is because we do not detect significant correlation between the gust parameters from the measurements in all four regions. Thus, the non-diagonal terms of R are 0. The 50-year return surface
345 for the data from the United States of America is shown in Fig. 10. The return surface is subsequently sampled to generate wind boxes as described in Sect. 2.5. The results of the aero-elastic simulations are presented in the next section.

By applying the inverse Nataf transform, as shown by Hannesdóttir et al. (2023), we can also estimate the return period of the ECD, T_{ECD} , in the four regions. The values of T_{ECD} are shown in Table 6. We find that the return periods are an order of magnitude longer than 50 years. We also note that while thunderstorm-driven gusts are more frequent in United States, as
350 indicated by the value of λ , they are less severe than the events occurring in Australia which has the lowest return period for the ECD. Note that the uncertainty in the estimates of T_{ECD} is quantified in Appendix C. Although, the results have a large spread, the minimum return period in all four cases is always longer than 50 years.

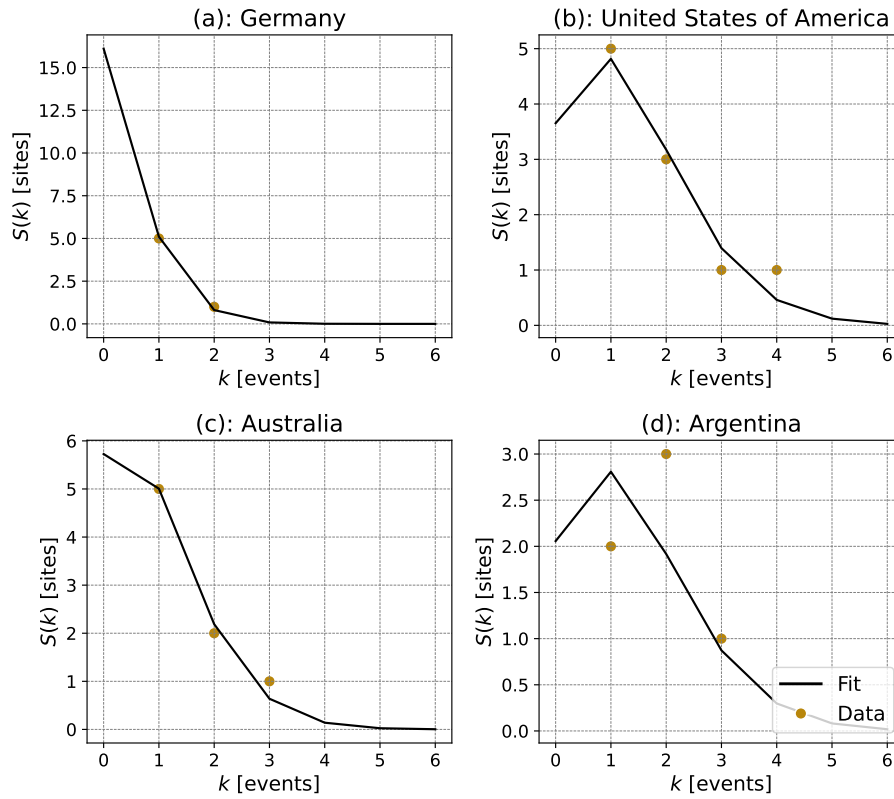


Figure 8. Poisson distribution fitted to the number of sites, S , as a function of the number of events at that site, k .

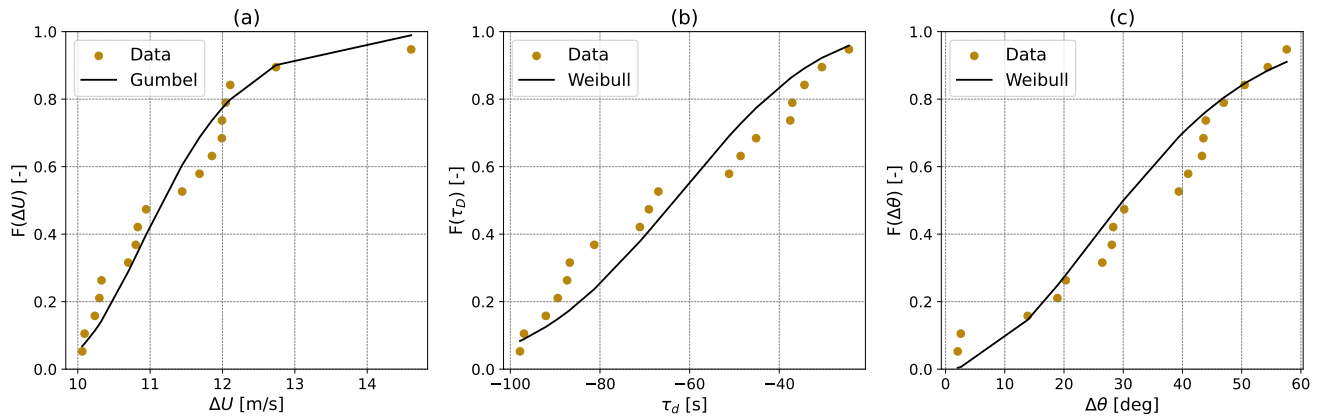


Figure 9. Marginal distributions fitted to the wind speed changes (ΔU), rise times (τ_d) and wind direction changes ($\Delta\theta$) of the 18 cold pool events detected in the United States of America.

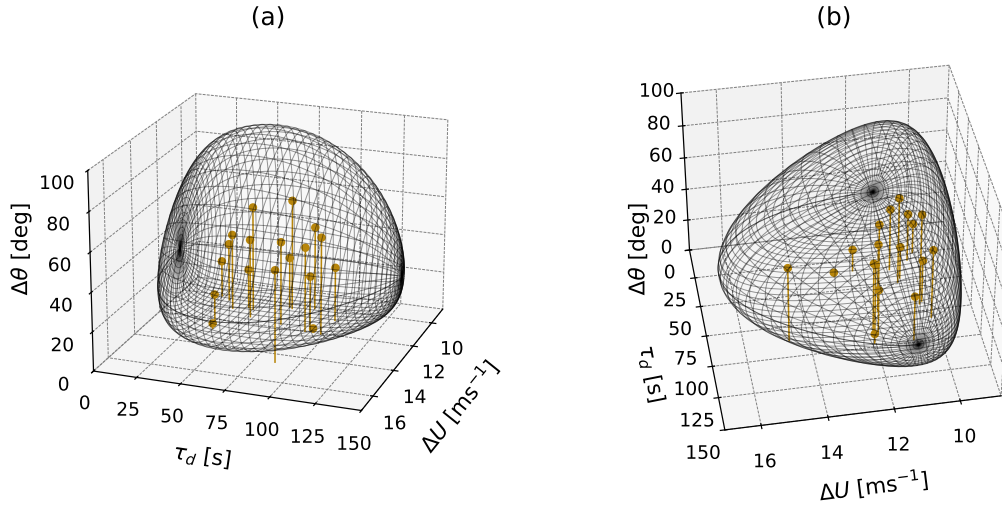


Figure 10. Two different views of the 50-year return surface obtained from the 18 cold pool events detected in the United States of America. Note that the vertical lines from the data points intersect the $\tau_d - \Delta U$ plane at $\Delta\theta = 0^\circ$.

Region	λ [-]	MSE [-]	S_T [-]	T_m [yrs]	T_{ECD} [yrs]
United States of America	1.32	0.12	14	21	2085
Argentina	1.37	0.35	8	12	578
Australia	0.87	0.22	14	21	285
Germany	0.32	0.06	22	29	449

Table 6. The average rate of occurrence of events at a site (λ), the total number of sites (S_T), the equivalent length of the dataset in time (T_m) and the return period of the ECD (T_{ECD}) for the four regions analysed in this study.

3.5 An analysis of dynamic loads

3.5.1 Loads measured from the fleet

355 The dataset also contains measurements of flapwise blade bending moments taken at the root of the all three blades. Note that tower-base moments were not recorded. The measurements are stored as 10 min maxima and are presented in Fig. 11. The violin plots represent the distribution of the maximum 10 min flapwise moment over all three blades taken from all 10 min periods up to 5 days before and after the event. Thus, it represents the background load conditions under which the event occurs. The maximum loads associated with the events are indicated in the figure by the circles. Note that only those events wherein

360 the loads were above a certain threshold have been shown in the figure. Moreover, the absolute values have been anonymized by dividing with the maximum flapwise moment over all events.

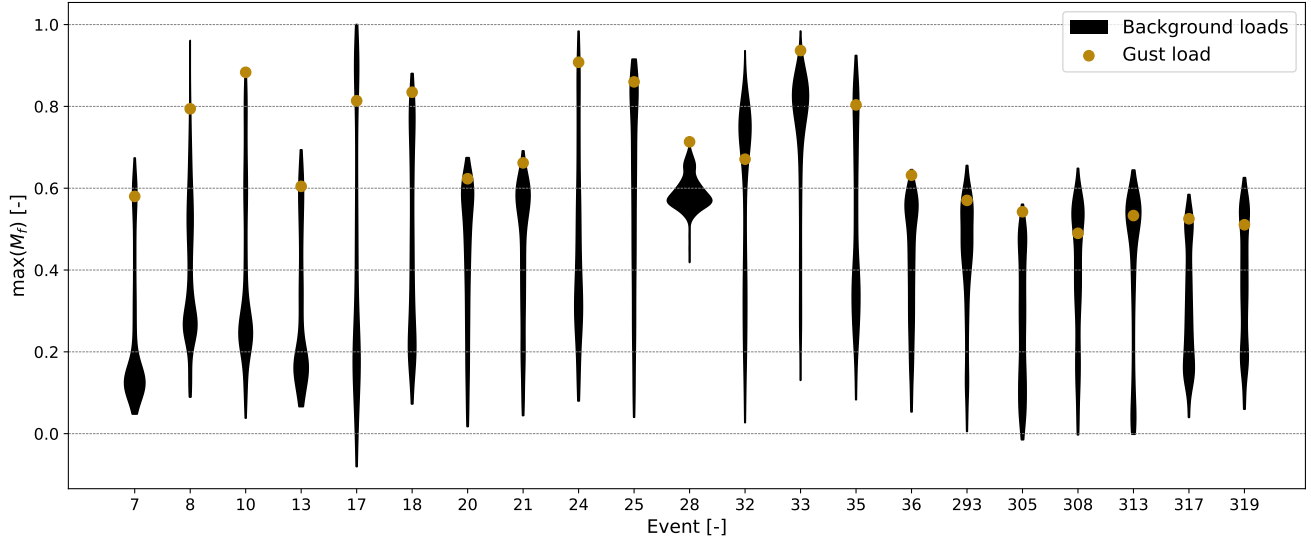


Figure 11. The 10 min maximum flapwise bending moment at the blade root during the cold pool events, denoted as the "gust load", compared to the maxima from all 10 min periods 5 days before and after the event, called the "background loads". Note that a subset of the 75 events are displayed in this figure, wherein the gust loads were above a certain threshold.

The maximum flapwise loads caused by the events fall at the tail end of the load distribution. However, they do not represent the highest flapwise moments experienced by the respective turbines over the 10 day period, except for events 10, 28 and 36. For these cases, we also compared the gust-driven flapwise moments to those measured over the current operational lives of the three turbines (which were 2, 3 and 1.5 years respectively). We found that the gust-driven events had smaller flapwise loads compared to the maximum over this extended period of time.

3.5.2 Simulation of the 50-year return surface

The events sampled from the 50-year return surface were simulated in an aero-elastic solver to evaluate the response of the turbine, especially when compared to the ECD. We sampled the return surface obtained from the measurements (and shown in Fig. 10) in the United States of America at a resolution of 3 ms^{-1} , 10 s and 20° . This meant that each sampled event differed by at least 3 ms^{-1} or 10 s or 20° . The sampled subset, which consisted of 94 events, was used to create wind boxes as outlined in Sect. 2.5. Note that the simulations are 300 s in duration with the gust arriving at the rotor plane at $150\text{s} - \frac{\tau_d}{2}$. Moreover, the starting wind speed is $u_r - 2 \text{ ms}^{-1}$ where u_r is the rated wind speed of the turbine and 6 turbulence seeds are simulated for each event.

All simulations were performed on the V162 turbine. It is an onshore turbine with a rated power output of 7.2 MW , a rotor diameter of 162 m and a hub height of 169 m . Given the sensitivity of the tower to extreme changes in wind speed and direction,



Region	ΔU [ms^{-1}]	τ_d [s]	$\Delta\theta$ [$^\circ$]	ΔM_{TB}^{res} [%]
United States of America	11	7	30	-28
Argentina	12	5	42	-25
Australia	11	5	46	-27
Germany	12	14	30	-57

Table 7. The wind speed change (ΔU), rise time (τ_d) and direction change ($\Delta\theta$) for the fastest events on the 50-year return surfaces in all four regions along with the percentage reduction in maximum resultant tower moments as compared to the ECD.

we analysed the resultant bending moments at the bottom of the tower. The resultant moment, M_{TB}^{res} is defined as:

$$M_{TB}^{res} = \sqrt{(M_{TB}^{fa})^2 + (M_{TB}^{ss})^2}, \quad (21)$$

where M_{TB}^{fa} and M_{TB}^{ss} are the fore-aft and side-to-side bending moments respectively.

380 We characterize the load response by determining the maximum bending moment between $t = 140$ to 160 s, which had a prominence above a certain threshold. This window and threshold was chosen because it helped identify those cases where the event caused a sudden increase in the tower loads. Load peaks outside this window were found not to be driven by the gusts. Hence, these criteria made the results easier to interpret by establishing a one to one correspondence with the characteristics of the events.

385 Figure 12 presents the maximum resultant bending moments at the tower bottom for 94 events, averaged over all 7 seeds of a single event. We observed that many events with $\tau_d > 30$ s did not cause a load maxima. On other hand, there exists a nearly linear relationship between the rise time and the maximum bending moments for $\tau_d < 30$ s. Indeed, the highest loads were obtained from the events with the fastest rise time of 7 s. The rise time appears to be the most important characteristic when assessing the potential load impact of a certain event. As seen in the figure, events with $\Delta U > 15 \text{ ms}^{-1}$ or $\Delta\theta \geq 60^\circ$
 390 do not cause a load peak, if the rise time is not sufficiently fast. However, at rise times in the order of a few seconds, we do expect the wind speed and direction changes to play an important role. This is illustrated by comparing the maximum bending moments obtained from the fastest event in the sampled subset to those produced by the ECD. Similar observations were made by Hannesdóttir et al. (2023).

Table 7 shows the fastest events from the 50-year return surfaces in United States, Argentina, Australia and Germany as
 395 well as the percentage reduction in maximum tower bottom bending moments as compared to the ECD. While the rise times of these events are comparable, or even faster than the ECD, the wind speed and direction changes are approximately 4 ms^{-1} and 40° lower respectively. Thus, bending moments reduce by 25 - 28 % in United States, Argentina and Australia while they decrease by 57 % in Germany where the fastest event is less severe than the ECD in all three gust parameters.

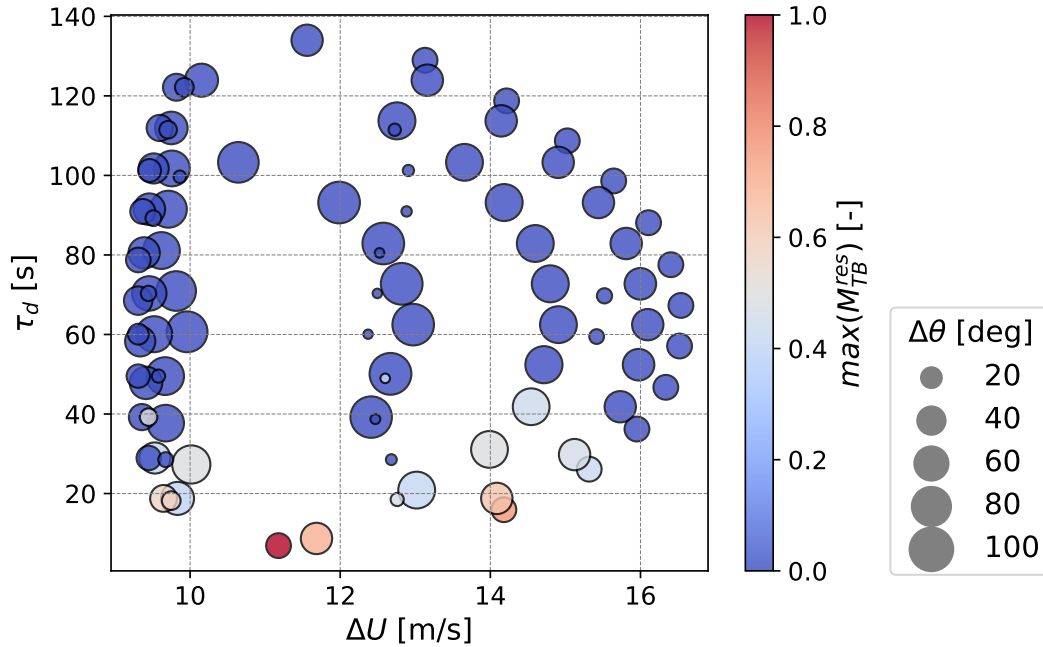


Figure 12. The maximum resultant bending moments on the bottom of the tower during the 94 events sampled from the 50-year return surface in the United States of America and simulated in an aeroelastic solver.

4 Discussion and conclusions

We present measurements of extreme changes in wind speed and direction observed across a fleet of wind turbines. The rotor-averaged wind speed is reconstructed using the torque or power balance equation (Soltani et al., 2013), a method validated for measuring wind speed ramps in Patel et al. (2026). We refer to this method as the wind speed estimator. Patel et al. (2026) showed that the wind speed estimator does not capture the same rise time as an anemometer when the gust exhibits shear, wherein the gust does not arrive at the same instant across all vertical points on the rotor plane. However, if the event is coherent, measurements from the wind speed estimator and the anemometer agree. In this study, we attempted to detect shear in the events by comparing rise times from the wind speed estimator to the nacelle anemometer. Given the noise inherent in nacelle anemometer measurements, we were unable to reach definitive conclusions about whether the detected events were coherent. We therefore assume all events are coherent. Based on the results in Appendix B, this assumption is conservative from a loads perspective.

The dataset comprised 319 turbines installed across 57 countries, which recorded 356 events over a 1.5-year period. Of these, 119 events were comparable to the ECD, exhibiting a ramp-like increase in wind speed. The remaining 237 events were gusts occurring during turbulent conditions, likely caused by an extratropical cyclone or tropical depression, in which the wind speed and direction time series resembled the extreme turbulence model of IEC (2019). Among the 119 wind ramp events,



75 were caused by thunderstorm outflow, identified by a simultaneous temperature drop of at least 2°C. Of the remaining 44
415 events, 27 occurred in highly complex terrain and were likely driven by terrain-related flow effects; the mechanism behind
the remaining 17 events could not be identified. This study focused on the 75 thunderstorm-driven events, as they frequently
exhibited wind direction changes greater than 30°, and because the size of this regional dataset was sufficient to apply the prob-
abilistic gust model developed by Hannesdóttir et al. (2023). Consequently, our results do not extend to sites in very complex
terrain. Although none of the 27 complex-terrain events shared the ECD's gust characteristics, we cannot draw conclusions
420 about whether the ECD's 50-year return period holds at such sites. Another limitation of the study concerns turbines installed
offshore. Our dataset included only 11 offshore turbines and consequently no offshore wind ramps were observed. Since the
turbulence offshore is lower than onshore, we can expect shorter rise times as the boundary of the gravity current could be
thinner than it is onshore. Moreover, there are likely a number of offshore atmospheric processes, such as open convective
cells, that can cause ramps in wind speed and direction. Therefore, we are uncertain about the conservatism of the ECD in this
425 environment.

We applied the probabilistic model to events detected in four regions: the United States, Argentina, Australia, and Germany.
As described in Sect. 2.4, we combined 1.5 years of measurements from multiple sites within each region by fitting the data
to a Poisson distribution. This allowed us to assume that events across S_T sites were identically and independently distributed,
such that the dataset's total effective length in time was $1.5S_T$ years. The probabilistic model showed that the ECD had a
430 return period exceeding 200 years in all four regions. Using the mean occurrence rate of thunderstorm-driven gusts in these
regions, we further showed that such events do not occur with comparable frequency in Brazil, Turkey, the United Kingdom,
and a few other regions. This allows us to classify regions into two categories: one in which cold pool events are rare, and
another in which they are common but produce wind conditions less severe than the ECD. Regions in the first category likely
have climates unfavourable for the formation of long-lived mesoscale convective systems, while in the second, the conditions
435 required to generate a gravity current capable of producing ECD-like wind speed and direction changes simply do not occur as
often as once every 50 years. Thus, our starting hypothesis – that the ECD is too conservative for the regions analysed in this
study – is strengthened. Moreover, our findings agree with those of Hannesdóttir et al. (2023) who found that the ECD had a
return period of 460 years at a coastal site in western Denmark.

We compared the 10-min maximum flapwise bending moments measured at the blade root during these events to the maxi-
440 mum loads experienced by this component over the surrounding 10-day period. The gust-driven bending moments fell within
the envelope of normal operation defined by this 10-day load distribution. Even in cases where gust-driven loads exceeded
this envelope, they did not surpass the maximum loads experienced by the turbine over its operational lifetime. The relative
benignity of the observed events, compared to the ECD, is therefore reflected in the blade flapwise moment measurements.
We suspect these findings generalize to tower bending moments as well; however, since loads on the tower were not directly
445 measured, future research could develop a digital twin of the tower (and other components) to better characterize the load
impact of wind ramps across the fleet. More broadly, future studies might investigate the cause of the highest loads recorded
over a turbine's operational lifetime, since these do not appear to be driven by cold pools.



We also simulated events on the 50-year return surface using an aeroelastic solver. To isolate the load impact of the gusts, we identified the maximum loads above a given threshold within a narrow window surrounding each event. This revealed that the fastest event on the return surface produced the highest bending moment at the tower base, while most events slower than 30 s did not produce a load maximum. To limit the scope of this study, we did not investigate the load effects of the initial wind speed or the temporal offset between wind speed and direction changes. Although the rise times of the fastest events on the 50-year return surfaces across all four regions were comparable to the ECD, the corresponding wind speed and direction changes were approximately 4 ms^{-1} and 40° lower, respectively. As a result, the maximum gust-driven bending moments on the tower were reduced by 25–28%. These findings on the ECD's over-conservatism apply to onshore sites in simple terrain within the regions studied, where cold pool events are the primary driver of extreme wind speed and direction changes. Since many turbines are installed at sites fitting this profile, this load reduction could translate into a meaningful improvement in the cost efficiency of wind turbines. We expect that the exact load reduction and the associated commercial value to be turbine and controller-specific and will therefore vary from one manufacturer to another.

In summary, our results highlight an over-conservatism in the current definition of the extreme coherent gust with direction change. We believe this study provides a solid step towards its revision.

Data availability. The data analysed in this study cannot be made available publicly.

Appendix A: Gravity currents and Froude number similarity

We computed the Froude number of the events detected by Hannesdóttir and Kelly (2019) at the Høvsøre test centre wherein the temperature dropped by at least 2°C over a period of 10 min and the rise time of the events was less than 150 s. The aim was to show the similarity of the Froude numbers to those obtained in other experimental studies of gravity currents (Simpson, 1999; Garratt, 1984). This comparison is not possible using the fleet data as we lack measurements of atmospheric pressure.

The Froude number, Fr , is defined as:

$$Fr = \frac{c}{\sqrt{g'h}}, \quad (\text{A1})$$

where c is the speed of the gravity current, h is the depth of the current and g' is reduced gravity acceleration, given by:

$$g' = \frac{\rho_2 - \rho_1}{\rho_1} g, \quad (\text{A2})$$

with ρ_2 and ρ_1 being the air densities of the cold and warm air columns close to the ground. The depth of the current can be approximated by the difference in hydrostatic pressure (Garratt, 1984):

$$h \approx \frac{P_2 - P_1}{g(\rho_2 - \rho_1)}. \quad (\text{A3})$$

Here, P is the pressure at ground level. We calculate the speed of the current as follows:

$$c \approx u_2 - u_1 \cos \Delta\theta, \quad (\text{A4})$$



Event	h [m]	ΔT [°C]	Fr [-]
1	444	-2.2	0.91
2	704	-2.1	1.34
3	509	-4.5	1.09
4	1009	-3.1	1.12

Table A1. The depth of the gravity current (h), the change in temperature (ΔT) and the Froude number (Fr) for four events detected in Høvsøre by Hannesdóttir and Kelly (2019).

where, u_1 and u_2 are the wind speeds before and after the current and $\Delta\theta$ is the direction change. This equation can be rewritten as:

$$c \approx \Delta U + 2u_1 \sin^2 \frac{\Delta\theta}{2}, \quad (\text{A5})$$

such that $\Delta U = u_2 - u_1$ is the wind speed change. Thus, this model of the current defines c as the relative speed of the current with respect to the ambient wind speed. Since the current does not necessarily travel in the same direction as the ambient wind, we take the projection of u_1 along the direction of travel of the current while calculating c . Moreover, we can relate c to two of three gust parameters.

The wind speed and direction are obtained from a cup anemometer and wind vane placed at a height of 100 m while the pressure is measured at 2 m and the temperature at 10 m.

The Froude numbers for the events are shown in Table A1. We find that the Fr is between 0.75 and 1.5, as predicted from theoretical considerations (Benjamin, 1968) and seen in experimental studies (Simpson, 1999; Garratt, 1984). As an example, we show how Fr for event 2 was calculated.

We first characterize the wind ramp via the method of Hannesdóttir and Kelly (2019) as shown in Fig. A1. The 3 gust variables, ΔU , τ_d and $\Delta\theta$ are 11.6 ms^{-1} , 70 s and 19° respectively. We then find the temperature and pressure changes by averaging the measurements shown in Fig. A2 and A3, 10 min before and after the event. The duration of the event is indicated by the vertical lines in the two figures. We then determine, c , g' , h and Fr .

Based on these results we have good reason to believe that the 75 events detected from the fleet data, wherein $\Delta T < 2^\circ\text{C}$, are caused by gravity currents formed from the outflow of thunderstorms.

Appendix B: Aero-elastic simulations of sheared and coherent gusts

In order to compare the load impact of sheared and coherent gusts, we performed two sets of simulations. One with a coherent gust wherein $\Delta U = 13 \text{ ms}^{-1}$, $\Delta\theta = 50^\circ$ and $\tau_d = 20 \text{ s}$. The sheared gust had the same magnitude of wind speed and direction change but $\tau_d = 10 \text{ s}$ and a 20 s shear. Thus, the gust arrived 20 seconds later at the bottom of the rotor compared to the top. Seven seeds were simulated in each case with the turbulence boxes generated via the procedure outlined in Section 2.5.

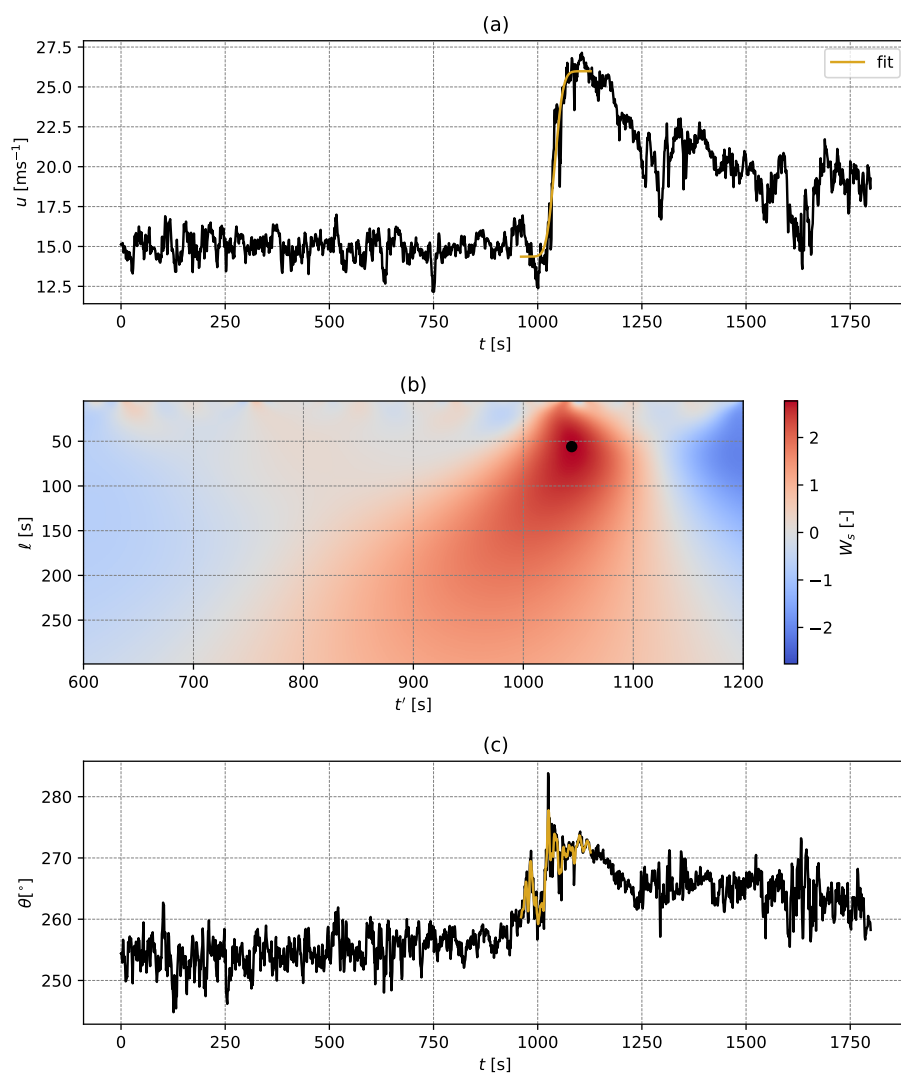


Figure A1. The gust detection and characterization method of Hannesdóttir and Kelly (2019) applied to Event 2 from Table A1.

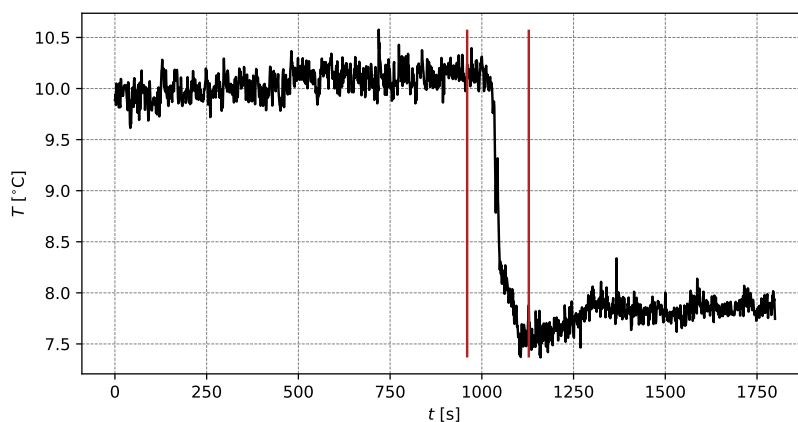


Figure A2. The time series of the temperature at 10 m height measured during Event 2 from Table A1. Note that the vertical lines indicate the duration of the event.

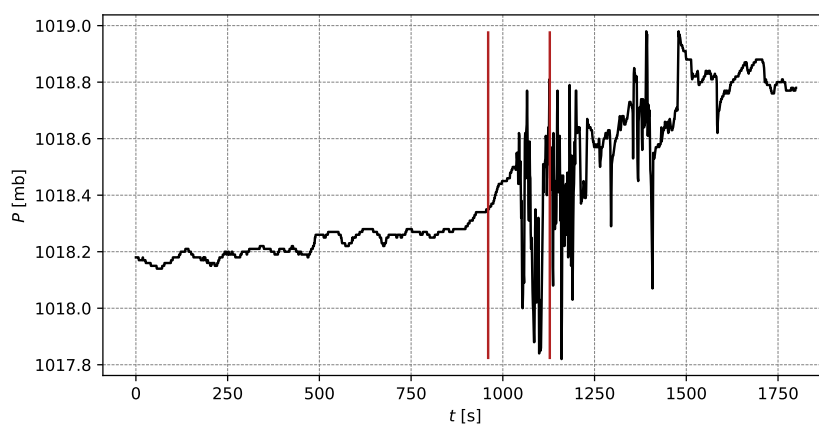


Figure A3. The time series of the pressure at 2 m height measured during Event 2 from Table A1. Note that the vertical lines indicate the duration of the event.

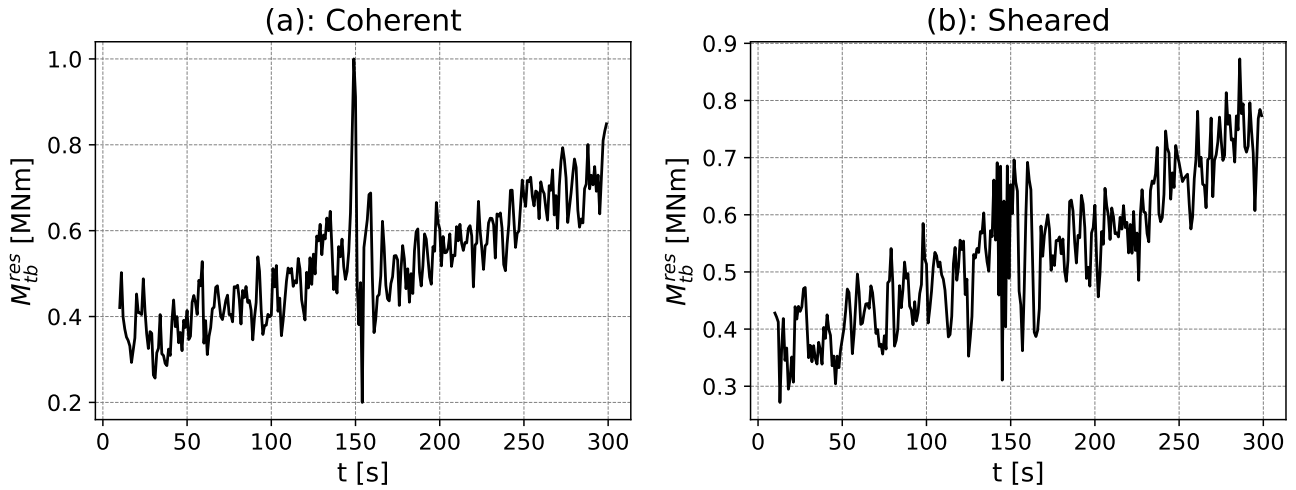


Figure B1. The time series of the resultant bending moment at tower bottom in the (a) coherent and (b) sheared gusts. Note that the data has been normalized by the maximum load value.

500 In Fig. B1, we show a comparison of the resultant moment at tower bottom which is calculated using Eq. 21, for a single seed. Indeed, in all seven seeds, we observe that the sheared gust does not cause a load peak.

A likely explanation for these results is that the controller receives an "early-warning" of the gust in the sheared case via change in wind speed at the top of the rotor. It can subsequently take load-mitigation actions to prevent a sudden rise in tower loads. On the other hand, in the coherent case, the wind speed changes simultaneously over the entire rotor which causes a
 505 sharp increase in the tower moment before the controller can intervene. Thus, we expect the results to be generally applicable.

Appendix C: Uncertainty in the extreme value extrapolation model

Herein, we attempt to quantify the uncertainty bounds for the estimates of the return period of the ECD, T_{ECD} , shown in Table 6. These are obtained by a bootstrapping procedure, wherein a subset of the data from each region is randomly selected and the probabilistic gust model is applied to this subset. We select 80% of the events in a certain region and repeat the procedure
 510 10 times to find the mean, minimum and maximum of T_{ECD} . The results are shown in Table C1.

Author contributions. Formulation of the research question: AP, KZ and JM. Initial brainstorming: AP, AH and JM. Data analysis and interpretation: AP, with assistance from all co-authors. First draft: AP. Re-writing and review: all co-authors.



Region	N_e [-]	N_{es} [-]	T_{ECD} mean [yrs]	T_{ECD} min [yrs]	T_{ECD} max [yrs]
United States of America	18	14	3717	7813	1057
Argentina	11	9	1893	190	5430
Australia	12	10	649	119	3046
Germany	7	6	1126	229	4215

Table C1. The uncertainty in the return period of the ECD, T_{ECD} for the four regions quantified by the mean, minimum and maximum of T_{ECD} obtained via bootstrapping. Note that N_e is the number of events in the region and N_{es} is the number of events in the subset.

Competing interests. JM is a chief editor of the *Wind Energy Science* journal. KZ and KR are employed by Vestas Wind System A/S. The authors have no other competing interests to declare.

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References

- 520 Abraham, A., Bodini, N., Hamilton, N., Hirth, B., Schroeder, J., and Moriarty, P.: Observations of wind ramps generated by thunderstorm outflows, *Wind Energy Science Discussions*, 2026, 1–24, <https://doi.org/10.5194/wes-2026-82>, 2026.
- Benjamin, T. B.: Gravity currents and related phenomena, *Journal of Fluid Mechanics*, 31, 209–248, <https://doi.org/10.1017/S0022112068000133>, 1968.
- Chai, W. and Leira, B. J.: Environmental contours based on inverse SORM, *Marine Structures*, 60, 34–51, <https://doi.org/https://doi.org/10.1016/j.marstruc.2018.03.007>, 2018.
- 525 Charba, J.: Application of Gravity Current Model to Analysis of Squall-Line Gust Front, *Monthly Weather Review*, 102, 140–156, [https://doi.org/10.1175/1520-0493\(1974\)102<0140:AOGCMT>2.0.CO;2](https://doi.org/10.1175/1520-0493(1974)102<0140:AOGCMT>2.0.CO;2), 1974.
- Colquhoun, J. R., Shepherd, D. J., Coulman, C. E., Smith, R. K., and McInnes, K.: The Southerly Burster of South Eastern Australia: An Orographically Forced Cold Front, *Monthly Weather Review*, 113, 2090 – 2107, [https://doi.org/10.1175/1520-0493\(1985\)113<2090:TSBOSE>2.0.CO;2](https://doi.org/10.1175/1520-0493(1985)113<2090:TSBOSE>2.0.CO;2), 1985.
- 530 Cook, N. J.: Automated classification of gust events in the contiguous USA, *Journal of Wind Engineering and Industrial Aerodynamics*, 234, 105 330, <https://doi.org/https://doi.org/10.1016/j.jweia.2023.105330>, 2023.
- Dimitrov, N., Pedersen, M., and Ásta Hannesdóttir: An open-source Python-based tool for Mann turbulence generation with constraints and non-Gaussian capabilities, *Journal of Physics: Conference Series*, 2767, 052 058, <https://doi.org/10.1088/1742-6596/2767/5/052058>, 2024.
- 535 Garratt, J. R.: Cold fronts and dust storms during the Australian summer 1982–83, *Weather*, 39, 98–103, <https://doi.org/https://doi.org/10.1002/j.1477-8696.1984.tb05473.x>, 1984.
- Hannesdóttir, Á. and Kelly, M.: Detection and characterization of extreme wind speed ramps, *Wind Energy Science*, 4, 385–396, <https://doi.org/10.5194/wes-4-385-2019>, 2019.
- 540 Hannesdóttir, Á., Kelly, M., and Dimitrov, N.: Extreme wind fluctuations: Joint statistics, extreme turbulence, and impact on wind turbine loads, *Wind Energy Science*, 4, 325–342, <https://doi.org/10.5194/wes-4-325-2019>, 2019.
- Hannesdóttir, Á., Verelst, D. R., and Urbán, A. M.: Extreme coherent gusts with direction change - probabilistic model, yaw control, and wind turbine loads, *Wind Energy Science*, 8, 231–245, <https://doi.org/10.5194/wes-8-231-2023>, 2023.
- Hansen, K. S. and Larsen, G. C.: Full scale experimental analysis of extreme coherent gust with wind direction changes (EOD), in: *Journal of Physics: Conference Series*, vol. 75, Institute of Physics Publishing, ISSN 17426596, <https://doi.org/10.1088/1742-6596/75/1/012055>, 2007.
- 545 Hansen, K. S., Vasiljevic, N., and Sørensen, S. A.: Resource data, <https://doi.org/https://doi.org/10.11583/DTU.c.5405292.v14>, 2021.
- IEC: IEC 61400-1 Ed4: Wind turbines - Part 1: Design requirements, Tech. rep., International Electrotechnical Commission, Geneva, Switzerland, 2019.
- 550 Kelly, M.: From standard wind measurements to spectral characterization: turbulence length scale and distribution, *Wind Energy Science*, 3, 533–543, <https://doi.org/10.5194/wes-3-533-2018>, 2018.
- Kristensen, L., Casanova, M., Courtney, M. S., and Troen, I.: In search of a gust definition, *Boundary-Layer Meteorology*, 55, 91–107, <https://doi.org/10.1007/BF00119328/METRICS>, 1991.
- Larsen, G. C. and Hansen, K. S.: Rational calibration of four IEC 61400-1 extreme external conditions, *Wind Energy*, 11, 685–702, <https://doi.org/https://doi.org/10.1002/we.302>, 2008.



- Leadbetter, M. R., Lindgren, G., and Rootzén, H.: *Extremes and Related Properties of Random Sequences and Processes*, Springer New York, 1 edn., ISBN 978-1-4612-5451-5, <https://doi.org/10.1007/978-1-4612-5449-2>, 1983.
- Letson, F., Barthelmie, R. J., Hu, W., and Pryor, S. C.: Characterizing wind gusts in complex terrain, *Atmospheric Chemistry and Physics*, 19, 3797–3819, <https://doi.org/10.5194/acp-19-3797-2019>, 2019.
- 560 Liu, P.-L. and Der Kiureghian, A.: Multivariate distribution models with prescribed marginals and covariances, *Probabilistic Engineering Mechanics*, 1, 105–112, [https://doi.org/10.1016/0266-8920\(86\)90033-0](https://doi.org/10.1016/0266-8920(86)90033-0), 1986.
- Mann, J.: Wind field simulation, *Probabilistic Engineering Mechanics*, 13, 269–282, [https://doi.org/10.1016/S0266-8920\(97\)00036-2](https://doi.org/10.1016/S0266-8920(97)00036-2), 1998.
- Müller, G. and Floors, R.: Home page [wetterzentrale.de](https://www.wetterzentrale.de), <https://www.wetterzentrale.de/en/contact.php>, 2026.
- Nataf, A.: Détermination des distributions dont les marges sont données, *Comptes Rendus de l'Académie des Sciences*, 225, 42–43, 1962.
- 565 NOAA National Centers for Environmental Information: Radar Data Map Viewer, <https://noaa.gov>, accessed: 2026-07-03, 2026.
- Patel, A., Mann, J., Sjöholm, M., Zinck, K., and Raj, K.: Characteristics of extreme wind ramps observed from a fleet of turbines, *Journal of Physics: Conference Series*, 2026.
- Rasmussen, K. L., Zuluaga, M. D., and Houze Jr., R. A.: Severe convection and lightning in subtropical South America, *Geophysical Research Letters*, 41, 7359–7366, <https://doi.org/10.1002/2014GL061767>, 2014.
- 570 Simpson, J.: *Gravity Currents 2nd Edition | Cambridge University Press & Assessment*, Cambridge University Press, 2nd edn., <https://www.cambridge.org/dk/universitypress/subjects/earth-and-environmental-science/oceanography-and-marine-science/gravity-currents-environment-and-laboratory-2nd-edition?format=PB&isbn=9780521664011>, 1999.
- Smith, B. T., Castellanos, T. E., Winters, A. C., Mead, C. M., Dean, A. R., and Thompson, R. L.: Measured Severe Convective Wind Climatology and Associated Convective Modes of Thunderstorms in the Contiguous United States, 2003–09, *Weather and Forecasting*, 575 28, 229 – 236, <https://doi.org/10.1175/WAF-D-12-00096.1>, 2013.
- Soltani, M. N., Knudsen, T., Svenstrup, M., Wisniewski, R., Brath, P., Ortega, R., and Johnson, K.: Estimation of rotor effective wind speed: A comparison, *IEEE Transactions on Control Systems Technology*, 21, 1155–1167, <https://doi.org/10.1109/TCST.2013.2260751>, 2013.
- Stork, C. H. J., Butterfield, C. P., Holley, W., Madsen, P. H., and Jensen, P. H.: Wind conditions for wind turbine design proposals for revision of the IEC 1400-1 standard, *Journal of Wind Engineering and Industrial Aerodynamics*, pp. 443–454, 1998.
- 580 Stull, R. B.: *Practical Meteorology : An Algebra-based Survey of Atmospheric Science*, Department of Earth, Ocean & Atmospheric Sciences, University of British Columbia, ISBN 9780888651761, <https://doi.org/10.14288/1.0300441>, 2015.
- Vanelli, T., Dellwik, E., Mann, J., Laan, M. P. v. d., Cavalli, M., Mirzaei, M., and Žagar, M.: How accurate is nacelle-based anemometry during intentional yaw misalignment? An experimental assessment from a near-ideal site, *Journal of Physics: Conference Series*, 3224, 022 026, <https://doi.org/10.1088/1742-6596/3224/2/022026>, 2026.
- 585 Wakimoto, R. M.: The Life Cycle of Thunderstorm Gust Fronts as Viewed with Doppler Radar and Rawinsonde Data, *Monthly Weather Review*, 110, 1060 – 1082, [https://doi.org/10.1175/1520-0493\(1982\)110<1060:TLCOTG>2.0.CO;2](https://doi.org/10.1175/1520-0493(1982)110<1060:TLCOTG>2.0.CO;2), 1982.
- Zipser, E. J., Cecil, D. J., Liu, C., Nesbitt, S. W., and Yorty, D. P.: Where are the most intense thunderstorms on Earth?, *Bulletin of the American Meteorological Society*, 87, 1057 – 1072, <https://doi.org/10.1175/BAMS-87-8-1057>, 2006.
- Øye, S.: Flex4 Simulation of Wind Turbine Dynamics,” *Proceedings of the 28th IEA Meeting of Experts Concerning State of the Art of*
- 590 *Aeroelastic Codes for Wind Turbine Calculations*, Tech. rep., International Energy Agency, 1996.